Journal of Machine Learning Research 1 (2000) 1-48 Submitted 4/00; Published 10/00

Accelerated oblique random survival forests

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Editor: TBD

Abstract

The oblique random survival forest (ORSF) is an ensemble method for supervised learning that extends the random survival forest (RSF). Trees in the ORSF are grown using linear combinations of variables to create branches in the tree, whereas in the RSF a single variable is used. ORSF ensembles often have higher prediction accuracy than RSF ensembles, but the additional computational overhead of fitting ORSF ensembles limits their scope of application. In addition, few methods have been developed for interpretation of ORSF ensembles. In this article, we introduce and evaluate methods to accelerate the ORSF (that is, reduce computational overhead) and compute the importance of individual variables in the ORSF We show that our strategy to accelerate the ORSF is up to 500 times faster than existing software for ORSFs (the `obliqueRSF` R package), and that prediction accuracy of the accelerated ORSF is equivalent or superior to that of existing ORSF methods. We estimate importance of variables for the ORSF by negating each coefficient used for the given variable in linear combinations, and then computing the reduction in out-of-bag accuracy. We show with simulation that 'negation importance' can discriminate between signal and noise variables, and it outperforms several state-of-the-art variable importance techniques in this task when there is correlation among predictors.

Keywords: Random Forests, Survival, Efficient, Variable Importance

1. Introduction

Risk prediction can reduce the burden of disease by educating patients and providers and guiding strategies to prevent and treat disease in a wide range of medical domains (Moons et al., 2012a,b). The random survival forest (RSF), a supervised learning algorithm that can engage with censored outcomes, is frequently used for risk prediction. Notable characteristics of the RSF include uniform convergence of its ensemble survival function to the true population survival function when the predictor space is discrete (Ishwaran and Kogalur, 2010). In addition, software implementing the RSF is freely available, extremely efficient, and full of tools to interpret and explain the RSF (Ishwaran and Kogalur, 2019; Wright and Ziegler, 2017; Hothorn et al., 2010). However, there remains considerable potential to improve the RSF in risk prediction tasks where training samples are not large enough to guarantee asymptotic properties or predictor spaces are non-discrete (that is, predictors are continuous).

RSFs may be axis based or oblique. The axis based RSF uses a single predictor whereas the oblique RSF uses a linear combination of predictors to create branches in trees. While axis based decision boundaries are always perpendicular to the axis of the relevant predictor, linear combinations of predictors create oblique decision boundaries that are neither parallel nor perpendicular to axes of their contributing predictors. Prior work has found the oblique RSF has higher prediction accuracy than the axis based RSF in general benchmarks (Jaeger et al., 2019) and that oblique splitting is particularly effective when predictors are continuous (Menze et al., 2011). However, existing methods to implement oblique splitting typically use fully trained models in each non-leaf node to identify linear combinations of predictors, exponentially increasing the number of operations required for the oblique RSF versus its axis based counterpart. In addition, standard methods to estimate variable importance (VI) in the RSF are less effective in the oblique RSF, and few methods have been introduced to estimate VI specifically for the oblique RSF.

The aim of this article is to improve the computational efficiency and interpretability of the oblique RSF. In a general benchmark experiment including YYYY risk prediction tasks, we show that oblique RSFs with partially trained models have equivalent or superior prediction accuracy and are orders of magnitude more efficient than oblique RSFs with fully trained models in non-leaf nodes. We introduce a method to estimate VI for oblique RSFs and compare its ability to discriminate between signal and noise variables versus standard and state-of-the-art methods. All methods proposed in this article are available in the `aorsf` R Package.

2. Related work

2.1 Axis-based and oblique random forests

After Breiman (2001) introduced the axis-based and oblique random forest (RF), numerous methods were developed to grow oblique RFs for classification or regression tasks (Menze et al., 2011; Zhang and Suganthan, 2014; Rainforth and Wood, 2015; Zhu et al., 2015; Poona et al., 2016; Qiu et al., 2017; Tomita et al., 2020; Katuwal et al., 2020). However, oblique splitting approaches for classification or regression may not generalize to survival tasks (for example, see Zhu, 2013, Section 4.5.1), and most research involving the RSF has focused on forests with axis-based trees (Wang and Li, 2017).

Building on prior research for bagging survival trees (Hothorn et al., 2004), Hothorn et al. (2006) developed an axis-based RSF in their framework for unbiased recursive partitioning, more commonly referred to as the conditional inference forest (CIF). Zhou et al. (2016) developed a rotation forest based on the CIF and Wang and Zhou (2017) developed a method for extending the predictor space of the CIF. Ishwaran et al. (2008) developed an axis-based RSF with strict adherence to the rules for growing trees proposed in Breiman (2001). Jaeger et al. (2019) developed the oblique RSF following the bootstrapping approach described in Breiman's original RF and incorporating early stopping rules from the CIF.

2.2 Variable importance

Breiman (2001) introduced permutation VI, defined for each predictor as the difference in a RF's estimated generalization error before versus after the predictor's values are randomly permuted. Strobl et al. (2007) identified bias in permutation VI driven by variable selection bias and effects induced by bootstrap sampling, and proposed an unbiased permutation VI based on unbiased recursive partitioning (see Hothorn et al. (2006)). Menze et al. (2011) introduced an approach to estimate VI for oblique RFs that computes an analysis of variance (ANOVA) table in non-leaf nodes to obtain p-values for each predictor contributing to the node. The ANOVA VI[1] is then defined for each predictor as the number of times a p-value associated with the predictor is ≤ 0.01 while growing a forest. Lundberg and Lee (2017) introduced a method to estimate VI using SHapley Additive exPlanation (SHAP) values, which estimate the contribution of a predictor to a model's prediction for a given observation. SHAP VI is computed for each predictor by taking the mean absolute value of SHAP values for that predictor across all observations in a given set.

3. Novel techniques for oblique random survival forests

3.1 Partial training at non-leaf nodes

Consider the usual framework for survival analysis with training data

$$\mathcal{D}_{\text{train}} = \{(T_i, \delta_i, \boldsymbol{x}_i)\}_{i=1}^{N_{\text{train}}}.$$

Here, T_i is the event time if $\delta_i = 1$ and last point of contact if $\delta_i = 0$, and $\boldsymbol{x}_i$ is a vector of predictors values. Assuming there are no ties, let $t_1 < \ldots < t_m$ denote the m unique event times in $\mathcal{D}_{\text{train}}$. We propose to identify linear combinations of predictor variables in non-leaf nodes by applying Newton Raphson scoring to the partial likelihood function of the Cox regression model:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{m} \frac{e^{\boldsymbol{x}_{j(i)}^T \boldsymbol{\beta}}}{\sum_{j \in R_i} e^{\boldsymbol{x}_j^T \boldsymbol{\beta}}}, \tag{1}$$

where R_i is the set of indices, j, with $T_j \geq t_i$ (i.e., those still at risk at time t_i), and $j(i)$ is the index of the observation for which an event occurred at time t_i. The `survival` package includes documentation that outlines how to complete this estimation procedure efficiently (see Therneau, 2022, exact.nw). Briefly, a vector of estimated regression coefficients, $\hat{\beta}$, is updated in each step of the procedure based on its first derivative, $U(\hat{\beta})$, and second derivative, $H(\hat{\beta})$:

$$\hat{\beta}^{k+1} = \hat{\beta}^k + U(\hat{\beta} = \hat{\beta}^k)\, H^{-1}(\hat{\beta} = \hat{\beta}^k)$$

It is vital to cycle through iterations until a convergence threshold is met for statistical inference, but it is only necessary to complete one iteration to identify coefficients for a linear combination of predictors. Jaeger et al. (2019) identified linear combinations using penalized regression models, which supply more flexible solutions for $\hat{\beta}$ at the cost of greater computational demand.

3.2 Negation variable importance

Negation VI is similar to permutation VI in that it measures how much a model's prediction error increases when a variable's role in the model is de-stabilized. More specifically,

1. Menze et al. (2011) name their method 'oblique RF VI', but we use the name 'ANOVA VI' in this article to avoid confusing Menze's approach with other approaches to estimate VI for oblique RFs.

negation VI measures the increase in an oblique RF's prediction error after flipping the sign of all coefficients linked to a variable (that is, negating them). As the magnitude of a coefficient increases, so does the probability that negating it will change the oblique RF's predictions. Since the coefficients in each non-leaf node of an oblique RFs are adjusted for the accompanying predictors, negation VI may provide better estimation of VI in the presence of correlated variables compared to standard VI techniques. Although the current article focuses on oblique RSFs, negation VI can be applied to any oblique RF.

4. Numeric experiments

4.1 Benchmark of prediction accuracy

4.1.1 Learners

In the current study, we consider four classes of learners: RFs, boosting ensembles, regression models, and neural networks (Table 1). For RF learners, the number of observations required in terminal nodes was fixed at 10, the number of randomly selected predictors was the square root of the total number of predictors rounded to the nearest integer, and the number of trees in the ensemble was 500. For boosting and regression learners, nested cross-validation was applied to identify the number of boosting steps and the magnitude of penalization, respectively.

Learner Class	Software	Learners	Description
Random Survival Forests			
Standard	`RandomForestSRC`	`rfsrc-standard`	Axis based survival trees following Leo Breiman's original random forest algorithm, with cut-points selected to maximize a log-rank statistic.

Oblique	`obliqueRSF`
	`aorsf`
		`obliqueRSF-net`
		`aorsf-net`
		`aorsf-cph`$(i = 1)$
		`aorsf-cph`$(i \leq 15)$
		`aorsf-extratrees`
			Oblique survival trees following Leo Breiman's random forest algorithm. Linear combinations of inputs are derived using `glmnet` in `obliqueRSF-net` and `aorsf-net`, using Newton Raphson scoring for the Cox partial likelihood function in `aorsf-cph`$(i = 1)$ and `aorsf-cph`$(i \leq 15)$, and chosen randomly from a uniform distribution in `aorsf-extratrees`. Cut-points are selected to maximize a log-rank statistic.

Extremely Randomized	`ranger`	`ranger-extratrees`	Axis-based survival trees grown with randomly selected features and cut-points
Conditional Inference	`party`	`party-cif`	Axis based survival trees grown using unbiased recursive partitioning.
Boosting ensembles			
Trees	`xgboost`	`xgboost-cox`	The Cox partial likelihood function is maximized additively with decision trees. Nested cross validation (5 folds) is applied to tune the number of trees grown.
Models	`xgboost`	`xgboost-aft`	The accelerated failure time likelihood function is maximized additively with decision trees. Nested cross validation (5 folds) is applied to tune the number of trees grown.
Regression models			
Cox Net	`glmnet`	`glmnet-cox`	The Cox model is fit using an elastic net penalty. Nested cross validation (5 folds) is applied to tune penalty terms.
Neural networks			
Cox Time	`survivalmodels`	`nn-cox`	A neural network based on the proportional hazards model with time-varying effects

Table 1: Learning algorithms assessed in numeric studies

4.1.2 Evaluation of prediction accuracy

Our primary metric for evaluating the accuracy of predicted risk is the integrated and scaled Brier score (Graf et al., 1999). For observation i in the testing data, let $\widehat{S}(t \mid \boldsymbol{x}_i)$ be the predicted probability of survival up to a given prediction horizon of $t > 0$ and let $\boldsymbol{x}_i$ be the vector of predictor values. Define

$$\widehat{\text{BS}}(t) = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} \{\widehat{S}(t \mid \boldsymbol{x}_i)^2 \cdot I(T_i \leq t, \delta_i = 1) \cdot \widehat{G}(T_i)^{-1} + [1 - \widehat{S}(t \mid \boldsymbol{x}_i)]^2 \cdot I(T_i > t) \cdot \widehat{G}(t)^{-1}\}$$

where $\widehat{G}(t)$ is the Kaplan-Meier estimate of the censoring distribution. As $\widehat{\text{BS}}(t)$ is time dependent, integration over time provides a summary measure of performance over a range of plausible prediction horizons. The integrated $\widehat{\text{BS}}(t)$ is defined as

$$\widehat{\mathcal{BS}}(t_1, t_2) = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} \widehat{\text{BS}}(t) dt. \tag{2}$$

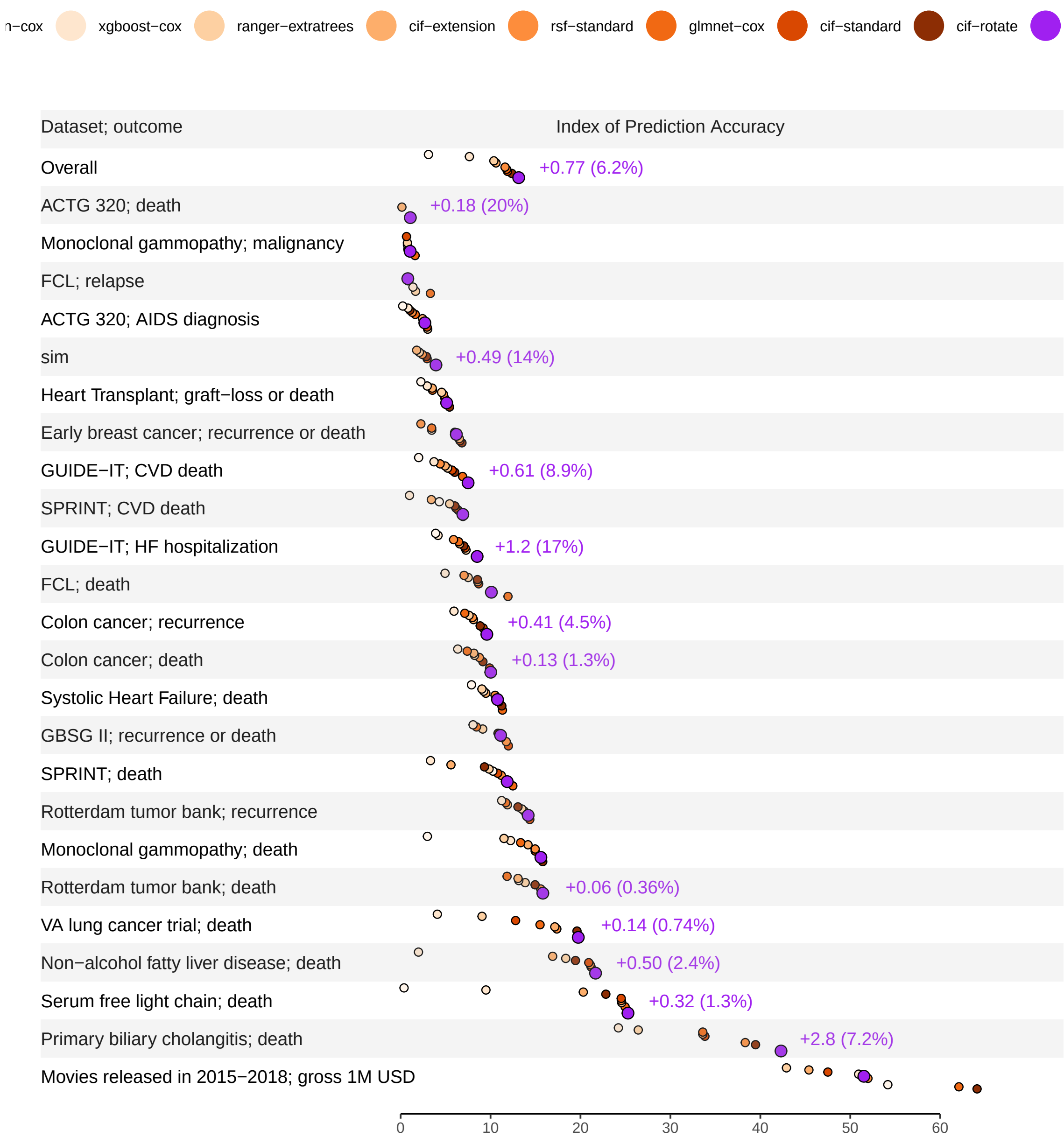
In our results, t_1 and t_2 are the 25th and 75th percentile of event times, respectively. $\widehat{\mathcal{BS}}(t_1, t_2)$, a sum of squared prediction errors, can be scaled to produce a measure of explained residual variation (that is, an R^2 statistic) by computing

$$R^2 = 1 - \frac{\widehat{\mathcal{BS}}(t_1, t_2)}{\widehat{\mathcal{BS}}_0(t_1, t_2)} \tag{3}$$

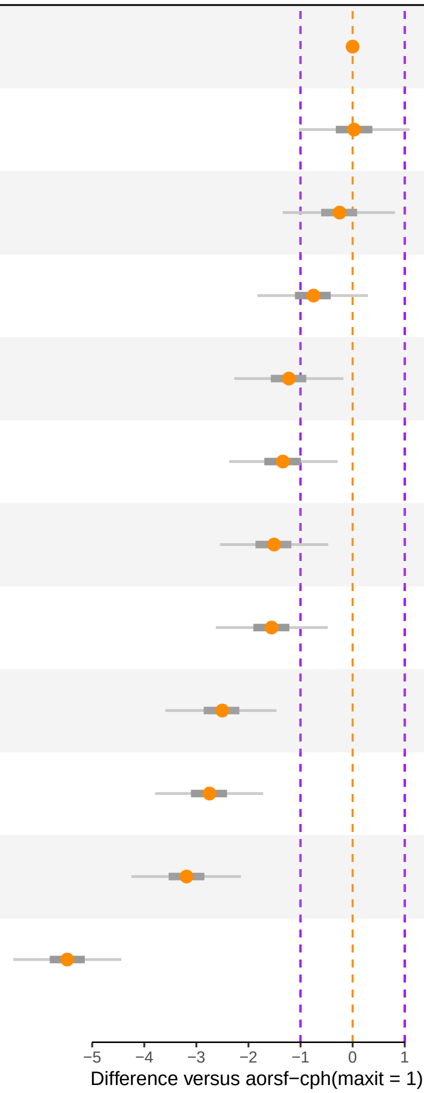
where $\widehat{\mathcal{BS}}_0(t_1, t_2)$ is the integrated Brier score when a Kaplan-Meier estimate for survival based on the training data is used as the survival prediction function $\widehat{S}(t)$. We refer to this R^2 statistic as the index of prediction accuracy and we scale its values by 100 to avoid unnecessary leading zero's. For example, we present 25 if R^2 is 0.25 and present 10.2 if the difference between two R^2 is 0.102.

4.1.3 Statistical analysis

4.1.4 Results


n−cox
xgboost−cox
ranger−extratrees
cif−extension
rsf−standard
glmnet−cox
cif−standard
cif−rotate
Dataset; outcome
Index of Prediction Accuracy
Overall
+0.77 (6.2%)
ACTG 320; death
+0.18 (20%)
Monoclonal gammopathy; malignancy
FCL; relapse
ACTG 320; AIDS diagnosis
sim
+0.49 (14%)
Heart Transplant; graft−loss or death
Early breast cancer; recurrence or death
GUIDE−IT; CVD death
+0.61 (8.9%)
SPRINT; CVD death
GUIDE−IT; HF hospitalization
+1.2 (17%)
FCL; death
Colon cancer; recurrence
+0.41 (4.5%)
Colon cancer; death
+0.13 (1.3%)
Systolic Heart Failure; death
GBSG II; recurrence or death
SPRINT; death
Rotterdam tumor bank; recurrence
Monoclonal gammopathy; death
Rotterdam tumor bank; death
+0.06 (0.36%)
VA lung cancer trial; death
+0.14 (0.74%)
Non−alcohol fatty liver disease; death
+0.50 (2.4%)
Serum free light chain; death
+0.32 (1.3%)
Primary biliary cholangitis; death
+2.8 (7.2%)
Movies released in 2015−2018; gross 1M USD
0
10
20
30
40
50
60

		Posterior probability	
Learner	Scaled integrated Brier score	Equivalence	Inferiority
aorsf−fast		0.00	0.00
aorsf−cph		0.94	0.48
aorsf−net		0.91	0.69
cif−rotate		0.68	0.93
cif−standard		0.32	0.99
glmnet−cox		0.25	0.99
rsf−standard		0.16	1.00
obliqueRSF−net		0.14	1.00
cif−extension		0.00	1.00
ranger−extratrees		0.00	1.00
aorsf−random		0.00	1.00
xgboost−cox		0.00	1.00

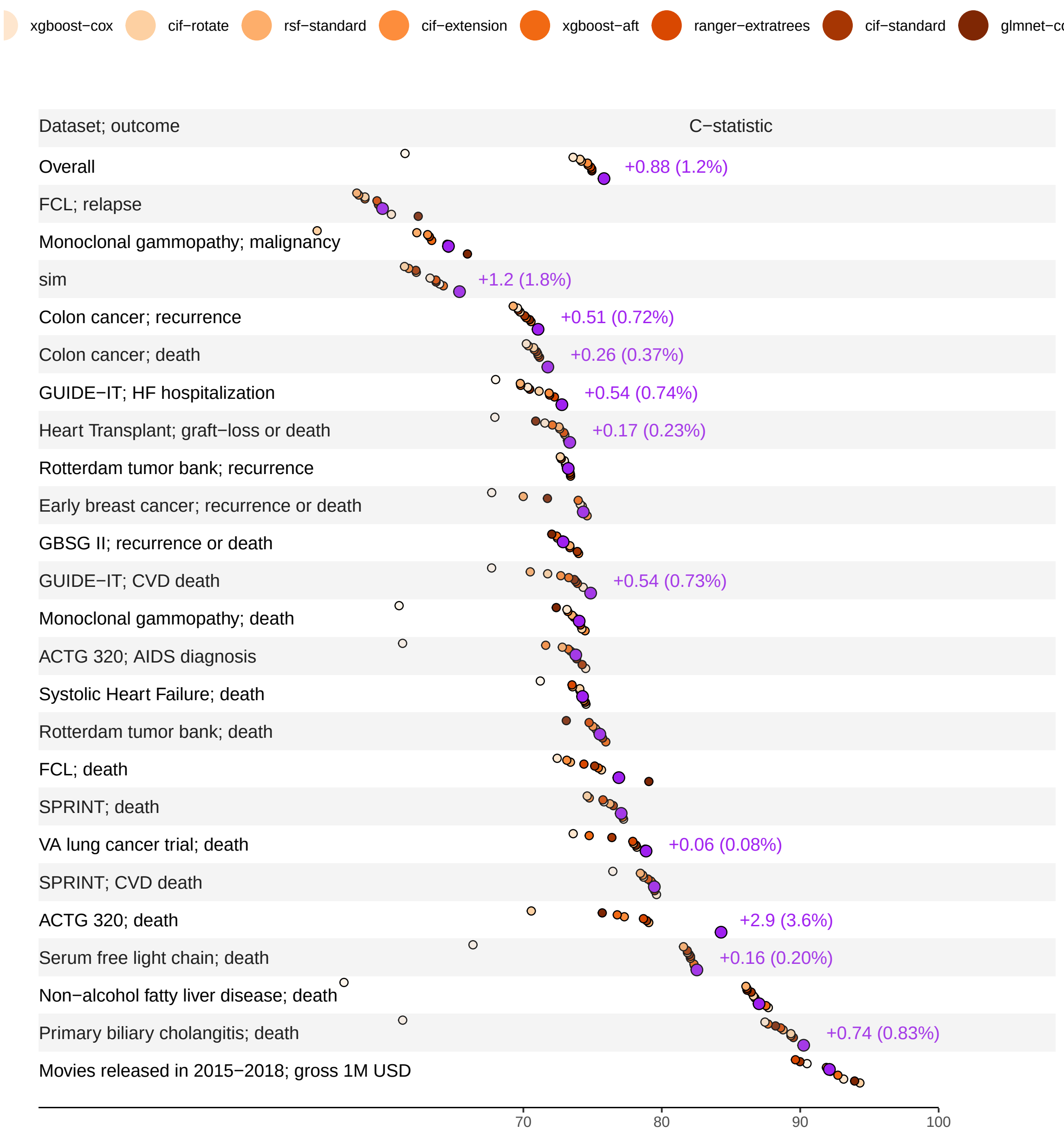


4.2 Benchmark of variable selection

Acknowledgments

Research reported in this publication was supported by the Center for Biomedical Informatics, Wake Forest University School of Medicine

Appendix A.


xgboost−cox
cif−rotate
rsf−standard
cif−extension
xgboost−aft
ranger−extratrees
cif−standard
glmnet−cc
Dataset; outcome
C−statistic
Overall
+0.88 (1.2%)
FCL; relapse
Monoclonal gammopathy; malignancy
sim
+1.2 (1.8%)
Colon cancer; recurrence
+0.51 (0.72%)
Colon cancer; death
+0.26 (0.37%)
GUIDE−IT; HF hospitalization
+0.54 (0.74%)
Heart Transplant; graft−loss or death
+0.17 (0.23%)
Rotterdam tumor bank; recurrence
Early breast cancer; recurrence or death
GBSG II; recurrence or death
GUIDE−IT; CVD death
+0.54 (0.73%)
Monoclonal gammopathy; death
ACTG 320; AIDS diagnosis
Systolic Heart Failure; death
Rotterdam tumor bank; death
FCL; death
SPRINT; death
VA lung cancer trial; death
+0.06 (0.08%)
SPRINT; CVD death
ACTG 320; death
+2.9 (3.6%)
Serum free light chain; death
+0.16 (0.20%)
Non−alcohol fatty liver disease; death
Primary biliary cholangitis; death
+0.74 (0.83%)
Movies released in 2015−2018; gross 1M USD
70
80
90
100

	Performance metric (SD)		Computing time, seconds			
			Fit model		Predict risk	
	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
Overall						
aorsf-cph	0.132 (0.123)	0.758 (0.077)	0.852	2.86	0.070	0.922
aorsf-fast	0.132 (0.123)	0.758 (0.077)	0.297	1.00	0.076	1.00
aorsf-net	0.130 (0.126)	0.756 (0.077)	68.335	229.9	0.071	0.930
cif-rotate	0.125 (0.144)	0.741 (0.090)	30.981	104.2	7.536	98.6
cif-standard	0.120 (0.110)	0.749 (0.076)	2.213	7.44	5.283	69.2
glmnet-cox	0.119 (0.136)	0.749 (0.079)	0.522	1.76	0.005	0.066
rsf-standard	0.117 (0.127)	0.741 (0.081)	1.713	5.76	0.149	1.95
obliqueRSF-net	0.116 (0.092)	0.755 (0.078)	334.542	1,125.4	26.565	347.7
cif-extension	0.107 (0.107)	0.746 (0.080)	13.591	45.7	7.281	95.3
ranger-extratrees	0.104 (0.096)	0.748 (0.074)	0.745	2.51	0.510	6.68
aorsf-random	0.100 (0.091)	0.735 (0.072)	2.063	6.94	0.068	0.888
xgboost-cox	0.077 (0.111)	0.737 (0.091)	3.846	12.9	0.005	0.066
nn-cox	0.031 (0.116)	0.615 (0.126)	15.466	52.0	1.652	21.6
xgboost-aft	-3.72 (4.96)	0.746 (0.079)	13.542	45.6	0.008	0.106
ACTG 320; AIDS diagnosis, n = 1151, p = 12						
aorsf-random	0.032 (0.014)	0.741 (0.030)	0.637	4.08	0.041	1.09
ranger-extratrees	0.030 (0.013)	0.737 (0.029)	0.067	0.429	0.184	4.83
cif-standard	0.029 (0.024)	0.743 (0.038)	1.608	10.3	4.825	126.9
obliqueRSF-net	0.029 (0.019)	0.739 (0.036)	30.556	195.7	16.658	438.0
aorsf-fast	0.027 (0.020)	0.738 (0.036)	0.156	1.00	0.038	1.00
aorsf-cph	0.027 (0.022)	0.744 (0.036)	0.460	2.94	0.035	0.921
cif-extension	0.024 (0.013)	0.716 (0.037)	11.131	71.3	5.866	154.2
aorsf-net	0.022 (0.027)	0.738 (0.036)	20.456	131.0	0.038	1.00
glmnet-cox	0.016 (0.025)	0.738 (0.030)	0.189	1.21	0.003	0.079
rsf-standard	0.013 (0.028)	0.728 (0.042)	0.212	1.36	0.083	2.17
cif-rotate	0.010 (0.033)	0.734 (0.034)	15.072	96.5	4.201	110.4
xgboost-cox	0.008 (0.029)	0.745 (0.033)	3.452	22.1	0.003	0.079
nn-cox	0.002 (0.012)	0.613 (0.089)	12.733	81.5	0.615	16.2
xgboost-aft	-7.79 (1.41)	0.733 (0.030)	11.574	74.1	0.007	0.184
ACTG 320; death, n = 1151, p = 12						
aorsf-fast	0.012 (0.021)	0.836 (0.045)	0.091	1.00	0.021	1.00
aorsf-cph	0.011 (0.020)	0.827 (0.052)	0.367	4.02	0.021	1.02
aorsf-random	0.009 (0.015)	0.804 (0.054)	0.318	3.48	0.028	1.34
obliqueRSF-net	0.008 (0.013)	0.829 (0.044)	9.819	107.6	10.716	520.0

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-net	0.005 (0.034)	0.815 (0.052)	14.708	161.2	0.025	1.19
cif-extension	0.001 (0.025)	0.764 (0.053)	9.440	103.4	4.147	201.2
ranger-extratrees	0.001 (0.023)	0.782 (0.061)	0.052	0.565	0.148	7.17
cif-standard	-0.004 (0.030)	0.777 (0.051)	1.818	19.9	4.470	216.9
xgboost-cox	-0.004 (0.003)	0.500 (0.000)	0.121	1.33	0.002	0.097
nn-cox	-0.005 (0.003)	0.541 (0.100)	12.682	139.0	0.665	32.3
rsf-standard	-0.019 (0.056)	0.781 (0.053)	0.091	0.992	0.043	2.06
cif-rotate	-0.038 (0.056)	0.701 (0.101)	14.054	154.0	3.602	174.8
glmnet-cox	-0.053 (0.100)	0.743 (0.092)	0.314	3.45	0.002	0.098
xgboost-aft	-24.5 (8.08)	0.757 (0.070)	11.563	126.7	0.009	0.419
Colon cancer; death, n = 929, p = 12						
aorsf-fast	0.100 (0.015)	0.718 (0.013)	0.289	1.00	0.078	1.00
aorsf-cph	0.099 (0.015)	0.716 (0.012)	0.685	2.37	0.070	0.909
cif-standard	0.099 (0.014)	0.712 (0.012)	1.571	5.44	5.267	67.9
aorsf-net	0.097 (0.014)	0.716 (0.012)	55.870	193.4	0.065	0.839
aorsf-random	0.095 (0.009)	0.715 (0.012)	2.500	8.65	0.066	0.852
cif-rotate	0.092 (0.018)	0.707 (0.014)	15.603	54.0	6.537	84.3
obliqueRSF-net	0.089 (0.007)	0.717 (0.012)	269.561	932.9	43.786	564.9
rsf-standard	0.088 (0.021)	0.703 (0.012)	1.646	5.70	0.143	1.85
ranger-extratrees	0.082 (0.007)	0.711 (0.012)	0.822	2.84	0.274	3.53
cif-extension	0.081 (0.006)	0.710 (0.012)	8.656	30.0	6.253	80.7
glmnet-cox	0.074 (0.013)	0.710 (0.017)	0.125	0.433	0.004	0.052
xgboost-cox	0.064 (0.011)	0.702 (0.012)	3.446	11.9	0.005	0.065
nn-cox	-0.006 (0.012)	0.504 (0.048)	15.123	52.3	2.166	27.9
xgboost-aft	-1.07 (0.231)	0.708 (0.013)	14.169	49.0	0.008	0.103
Colon cancer; recurrence, n = 929, p = 12						
aorsf-fast	0.096 (0.015)	0.711 (0.014)	0.276	1.00	0.070	1.00
aorsf-cph	0.095 (0.015)	0.710 (0.014)	0.704	2.55	0.070	0.994
aorsf-net	0.093 (0.017)	0.711 (0.016)	52.298	189.5	0.069	0.980
cif-standard	0.092 (0.015)	0.701 (0.015)	1.183	4.28	4.119	58.4
cif-rotate	0.088 (0.019)	0.698 (0.016)	14.170	51.3	5.936	84.2
obliqueRSF-net	0.087 (0.008)	0.711 (0.013)	328.771	1,191.0	45.669	648.0
aorsf-random	0.083 (0.012)	0.700 (0.014)	1.998	7.24	0.075	1.07
cif-extension	0.081 (0.009)	0.706 (0.013)	9.934	36.0	6.899	97.9
rsf-standard	0.080 (0.020)	0.693 (0.014)	1.308	4.74	0.135	1.92
ranger-extratrees	0.076 (0.012)	0.696 (0.012)	0.555	2.01	0.235	3.34
glmnet-cox	0.071 (0.014)	0.705 (0.020)	0.171	0.621	0.006	0.085

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
xgboost-cox	0.059 (0.011)	0.696 (0.014)	3.291	11.9	0.005	0.071
nn-cox	-0.006 (0.006)	0.511 (0.045)	14.010	50.8	1.651	23.4
xgboost-aft	-1.16 (0.238)	0.702 (0.015)	12.004	43.5	0.007	0.099
Early breast cancer; recurrence or death, n = 614, p = 1692						
obliqueRSF-net	0.070 (0.029)	0.748 (0.029)	1972.453	2,151.1	15.992	88.3
cif-rotate	0.070 (0.020)	0.746 (0.028)	6858.572	7,479.6	386.651	2,135.1
cif-standard	0.067 (0.022)	0.744 (0.030)	9.810	10.7	4.401	24.3
cif-extension	0.066 (0.017)	0.746 (0.027)	46.010	50.2	7.191	39.7
aorsf-cph	0.063 (0.038)	0.746 (0.028)	1.352	1.47	0.182	1.00
aorsf-fast	0.061 (0.037)	0.744 (0.027)	0.917	1.00	0.181	1.00
ranger-extratrees	0.059 (0.029)	0.741 (0.028)	0.245	0.267	0.180	0.994
xgboost-cox	0.040 (0.013)	0.745 (0.032)	2.231	2.43	0.007	0.036
glmnet-cox	0.035 (0.038)	0.721 (0.037)	5.766	6.29	0.006	0.031
aorsf-random	0.027 (0.018)	0.692 (0.038)	2.369	2.58	0.214	1.18
rsf-standard	0.020 (0.050)	0.699 (0.037)	0.404	0.440	0.662	3.65
aorsf-net	0.005 (0.080)	0.743 (0.025)	464.340	506.4	0.181	0.998
nn-cox	-0.017 (0.076)	0.679 (0.050)	18.858	20.6	1.907	10.5
xgboost-aft	-3.09 (0.743)	0.741 (0.021)	12.057	13.1	0.013	0.072
FCL; death, n = 541, p = 7						
glmnet-cox	0.119 (0.031)	0.791 (0.040)	0.133	1.48	0.003	0.150
aorsf-cph	0.102 (0.039)	0.769 (0.034)	0.175	1.94	0.020	1.00
aorsf-fast	0.101 (0.039)	0.769 (0.032)	0.090	1.00	0.020	1.00
aorsf-net	0.097 (0.041)	0.760 (0.037)	18.501	205.4	0.021	1.05
obliqueRSF-net	0.093 (0.027)	0.766 (0.038)	115.794	1,285.4	5.807	290.1
aorsf-random	0.090 (0.030)	0.763 (0.033)	0.319	3.54	0.020	1.00
cif-standard	0.087 (0.043)	0.752 (0.038)	1.227	13.6	1.275	63.7
cif-extension	0.086 (0.041)	0.731 (0.042)	6.649	73.8	2.610	130.4
cif-rotate	0.085 (0.051)	0.756 (0.028)	7.713	85.6	2.159	107.9
ranger-extratrees	0.075 (0.013)	0.744 (0.034)	0.038	0.425	0.087	4.33
rsf-standard	0.071 (0.056)	0.734 (0.039)	0.620	6.88	0.040	2.00
xgboost-cox	0.049 (0.055)	0.724 (0.097)	2.219	24.6	0.002	0.100
nn-cox	-0.001 (0.014)	0.548 (0.082)	12.668	140.6	0.510	25.5
xgboost-aft	-2.68 (0.479)	0.754 (0.044)	7.761	86.2	0.006	0.300
FCL; relapse, n = 541, p = 7						
glmnet-cox	0.033 (0.015)	0.624 (0.019)	0.101	0.791	0.002	0.074
ranger-extratrees	0.017 (0.018)	0.594 (0.029)	0.034	0.269	0.090	3.32
obliqueRSF-net	0.015 (0.015)	0.595 (0.023)	263.391	2,072.0	11.192	412.4

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
xgboost-cox	0.014 (0.014)	0.605 (0.029)	1.352	10.6	0.003	0.111
aorsf-random	0.013 (0.021)	0.599 (0.027)	0.530	4.17	0.025	0.922
aorsf-cph	0.009 (0.023)	0.600 (0.028)	0.272	2.14	0.028	1.04
cif-standard	0.008 (0.021)	0.595 (0.024)	1.143	8.99	1.784	65.7
aorsf-fast	0.008 (0.023)	0.598 (0.028)	0.127	1.00	0.027	1.00
aorsf-net	0.007 (0.024)	0.596 (0.029)	20.392	160.4	0.026	0.959
nn-cox	-0.003 (0.018)	0.535 (0.056)	13.504	106.2	0.781	28.8
cif-extension	-0.005 (0.026)	0.581 (0.030)	6.550	51.5	3.511	129.4
cif-rotate	-0.011 (0.026)	0.586 (0.031)	8.441	66.4	3.303	121.7
rsf-standard	-0.026 (0.034)	0.580 (0.027)	1.337	10.5	0.087	3.21
xgboost-aft	-0.826 (0.317)	0.586 (0.039)	7.490	58.9	0.007	0.258
GBSG II; recurrence or death, n = 686, p = 10						
obliqueRSF-net	0.120 (0.016)	0.741 (0.019)	334.738	1,750.9	12.512	271.2
cif-standard	0.120 (0.022)	0.739 (0.021)	1.134	5.93	2.323	50.4
aorsf-net	0.118 (0.027)	0.735 (0.022)	38.945	203.7	0.046	1.00
rsf-standard	0.117 (0.025)	0.734 (0.021)	1.872	9.79	0.112	2.42
aorsf-cph	0.113 (0.029)	0.729 (0.019)	0.441	2.30	0.047	1.02
cif-extension	0.112 (0.020)	0.740 (0.022)	8.962	46.9	4.709	102.1
aorsf-fast	0.111 (0.028)	0.729 (0.018)	0.191	1.00	0.046	1.00
cif-rotate	0.108 (0.025)	0.728 (0.018)	13.378	70.0	5.546	120.2
aorsf-random	0.100 (0.028)	0.718 (0.029)	1.373	7.18	0.047	1.02
ranger-extratrees	0.091 (0.020)	0.734 (0.028)	0.489	2.56	0.137	2.98
glmnet-cox	0.084 (0.018)	0.721 (0.021)	0.143	0.750	0.003	0.065
xgboost-cox	0.081 (0.017)	0.725 (0.019)	2.309	12.1	0.003	0.065
nn-cox	-0.004 (0.004)	0.505 (0.033)	12.705	66.5	1.348	29.2
xgboost-aft	-1.11 (0.152)	0.724 (0.022)	11.618	60.8	0.007	0.152
GUIDE-IT; CVD death, n = 894, p = 59						
aorsf-fast	0.075 (0.018)	0.749 (0.029)	0.181	1.00	0.037	1.00
aorsf-net	0.073 (0.017)	0.745 (0.029)	28.715	158.4	0.040	1.08
aorsf-cph	0.070 (0.019)	0.744 (0.029)	0.423	2.33	0.040	1.08
glmnet-cox	0.069 (0.037)	0.737 (0.071)	1.067	5.89	0.003	0.081
obliqueRSF-net	0.062 (0.014)	0.742 (0.025)	245.122	1,352.1	11.754	317.4
cif-rotate	0.060 (0.014)	0.718 (0.027)	37.291	205.7	4.865	131.4
cif-standard	0.057 (0.014)	0.738 (0.025)	2.289	12.6	3.756	101.4
ranger-extratrees	0.052 (0.014)	0.739 (0.031)	0.766	4.22	0.218	5.89
cif-extension	0.050 (0.013)	0.727 (0.024)	13.957	77.0	5.947	160.6
rsf-standard	0.044 (0.022)	0.705 (0.029)	1.611	8.89	0.075	2.03

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
xgboost-cox	0.037 (0.046)	0.743 (0.020)	4.400	24.3	0.003	0.081
aorsf-random	0.030 (0.013)	0.696 (0.030)	1.521	8.39	0.042	1.12
nn-cox	0.020 (0.040)	0.677 (0.093)	13.762	75.9	0.675	18.2
xgboost-aft	-5.15 (1.19)	0.733 (0.021)	15.383	84.9	0.007	0.189
GUIDE-IT; HF hospitalization, n = 894, p = 59						
aorsf-net	0.086 (0.017)	0.727 (0.025)	68.304	241.1	0.070	1.12
aorsf-fast	0.085 (0.018)	0.728 (0.027)	0.283	1.00	0.063	1.00
aorsf-cph	0.085 (0.020)	0.727 (0.025)	0.713	2.52	0.063	1.00
obliqueRSF-net	0.076 (0.011)	0.725 (0.024)	472.412	1,667.8	14.859	235.6
ranger-extratrees	0.073 (0.011)	0.722 (0.023)	0.801	2.83	0.514	8.15
cif-standard	0.072 (0.011)	0.719 (0.023)	2.043	7.21	3.784	60.0
cif-rotate	0.070 (0.020)	0.711 (0.031)	47.306	167.0	8.016	127.1
cif-extension	0.066 (0.009)	0.719 (0.021)	18.091	63.9	8.846	140.3
glmnet-cox	0.064 (0.019)	0.705 (0.024)	1.076	3.80	0.003	0.048
rsf-standard	0.059 (0.023)	0.698 (0.027)	1.775	6.27	0.109	1.73
aorsf-random	0.051 (0.011)	0.687 (0.025)	1.882	6.64	0.062	0.984
xgboost-cox	0.042 (0.014)	0.703 (0.027)	2.982	10.5	0.003	0.048
nn-cox	0.039 (0.032)	0.680 (0.077)	14.131	49.9	0.644	10.2
xgboost-aft	-2.22 (0.313)	0.698 (0.028)	12.951	45.7	0.007	0.111
Heart Transplant; graft-loss or death, n = 3787, p = 52						
cif-rotate	0.054 (0.011)	0.730 (0.019)	161.908	164.7	34.066	110.1
aorsf-net	0.051 (0.007)	0.731 (0.015)	132.397	134.7	0.313	1.01
aorsf-fast	0.051 (0.007)	0.734 (0.016)	0.983	1.00	0.309	1.00
aorsf-cph	0.051 (0.007)	0.732 (0.015)	3.094	3.15	0.311	1.01
cif-standard	0.049 (0.007)	0.732 (0.016)	12.017	12.2	46.520	150.3
obliqueRSF-net	0.048 (0.007)	0.729 (0.017)	362.862	369.2	168.051	543.1
rsf-standard	0.048 (0.010)	0.726 (0.013)	3.527	3.59	1.138	3.68
ranger-extratrees	0.046 (0.007)	0.729 (0.016)	4.963	5.05	3.527	11.4
glmnet-cox	0.035 (0.006)	0.709 (0.017)	1.023	1.04	0.013	0.042
cif-extension	0.035 (0.004)	0.726 (0.019)	50.426	51.3	24.989	80.8
xgboost-cox	0.030 (0.008)	0.716 (0.021)	3.520	3.58	0.011	0.036
aorsf-random	0.028 (0.003)	0.688 (0.014)	3.025	3.08	0.296	0.956
nn-cox	0.023 (0.011)	0.679 (0.023)	16.704	17.0	11.675	37.7
xgboost-aft	-4.38 (0.466)	0.721 (0.013)	13.594	13.8	0.008	0.026
Monoclonal gammopathy; death, n = 1384, p = 8						
cif-rotate	0.158 (0.020)	0.742 (0.015)	17.616	38.2	8.081	71.1
aorsf-cph	0.157 (0.015)	0.741 (0.010)	1.254	2.72	0.112	0.983

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-fast	0.156 (0.015)	0.740 (0.010)	0.461	1.00	0.114	1.00
obliqueRSF-net	0.154 (0.012)	0.742 (0.011)	244.591	530.3	17.341	152.5
aorsf-net	0.154 (0.014)	0.739 (0.010)	97.606	211.6	0.108	0.946
cif-standard	0.150 (0.014)	0.737 (0.011)	2.419	5.24	8.105	71.3
rsf-standard	0.150 (0.015)	0.735 (0.010)	1.834	3.98	0.182	1.60
aorsf-random	0.145 (0.013)	0.733 (0.011)	2.662	5.77	0.105	0.924
cif-extension	0.142 (0.009)	0.745 (0.012)	11.262	24.4	6.808	59.9
glmnet-cox	0.134 (0.019)	0.724 (0.013)	0.140	0.304	0.005	0.044
xgboost-cox	0.122 (0.012)	0.731 (0.012)	3.765	8.16	0.005	0.044
ranger-extratrees	0.115 (0.005)	0.741 (0.011)	0.098	0.212	0.645	5.68
nn-cox	0.030 (0.053)	0.610 (0.092)	15.851	34.4	1.194	10.5
xgboost-aft	-0.854 (0.157)	0.732 (0.013)	12.951	28.1	0.009	0.083
Monoclonal gammopathy; malignancy, n = 1384, p = 8						
glmnet-cox	0.016 (0.011)	0.660 (0.055)	0.119	0.558	0.003	0.069
aorsf-cph	0.011 (0.009)	0.648 (0.034)	0.626	2.94	0.044	1.02
aorsf-fast	0.011 (0.010)	0.646 (0.035)	0.213	1.00	0.044	1.00
cif-extension	0.008 (0.007)	0.631 (0.024)	11.659	54.8	5.776	132.5
aorsf-net	0.008 (0.011)	0.646 (0.034)	26.190	123.1	0.044	1.01
xgboost-cox	0.008 (0.013)	0.645 (0.039)	1.886	8.86	0.003	0.069
ranger-extratrees	0.008 (0.007)	0.646 (0.033)	0.071	0.334	0.888	20.4
obliqueRSF-net	0.007 (0.008)	0.634 (0.031)	49.465	232.5	17.992	412.8
aorsf-random	0.007 (0.012)	0.638 (0.033)	1.737	8.16	0.046	1.06
cif-standard	0.007 (0.008)	0.632 (0.031)	1.981	9.31	6.793	155.9
nn-cox	-0.005 (0.006)	0.501 (0.044)	12.103	56.9	1.392	31.9
rsf-standard	-0.009 (0.015)	0.623 (0.029)	0.906	4.26	0.074	1.70
cif-rotate	-0.026 (0.022)	0.551 (0.031)	13.529	63.6	4.724	108.4
xgboost-aft	-5.70 (1.21)	0.634 (0.041)	11.718	55.1	0.007	0.161
Movies released in 2015-2018; gross 1M USD, n = 551, p = 46						
cif-rotate	0.641 (0.024)	0.943 (0.007)	23.806	89.0	6.131	105.6
glmnet-cox	0.621 (0.034)	0.939 (0.010)	0.200	0.747	0.004	0.069
nn-cox	0.542 (0.072)	0.905 (0.030)	22.066	82.5	1.527	26.3
aorsf-net	0.531 (0.027)	0.928 (0.010)	68.367	255.5	0.061	1.05
aorsf-cph	0.523 (0.025)	0.925 (0.011)	0.812	3.04	0.060	1.04
rsf-standard	0.520 (0.023)	0.922 (0.011)	1.205	4.50	0.105	1.81
aorsf-fast	0.515 (0.027)	0.921 (0.013)	0.268	1.00	0.058	1.00
xgboost-cox	0.509 (0.025)	0.931 (0.010)	13.948	52.1	0.005	0.086
cif-standard	0.475 (0.027)	0.900 (0.018)	0.971	3.63	1.894	32.6

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
cif-extension	0.454 (0.027)	0.919 (0.013)	10.381	38.8	6.372	109.8
ranger-extratrees	0.429 (0.022)	0.897 (0.018)	0.079	0.295	0.975	16.8
obliqueRSF-net	0.320 (0.026)	0.907 (0.018)	157.741	589.5	27.372	471.5
aorsf-random	0.296 (0.034)	0.844 (0.029)	1.520	5.68	0.054	0.936
xgboost-aft	-0.449 (0.081)	0.927 (0.011)	54.157	202.4	0.009	0.155
Non-alcohol fatty liver disease; death, n = 17549, p = 24						
aorsf-cph	0.217 (0.009)	0.870 (0.005)	20.788	3.65	18.417	1.35
aorsf-fast	0.217 (0.009)	0.870 (0.005)	5.700	1.00	13.667	1.00
aorsf-net	0.214 (0.008)	0.866 (0.006)	502.140	88.1	10.280	0.752
obliqueRSF-net	0.213 (0.008)	0.870 (0.006)	1549.268	271.8	6853.986	501.5
glmnet-cox	0.212 (0.009)	0.862 (0.005)	2.153	0.378	1.017	0.074
rsf-standard	0.211 (0.009)	0.861 (0.005)	13.233	2.32	1.564	0.114
cif-standard	0.209 (0.007)	0.865 (0.006)	72.946	12.8	760.360	55.6
cif-rotate	0.194 (0.007)	0.866 (0.005)	292.104	51.2	235.407	17.2
ranger-extratrees	0.184 (0.007)	0.861 (0.005)	50.579	8.87	142.725	10.4
cif-extension	0.169 (0.002)	0.867 (0.006)	128.534	22.5	214.030	15.7
aorsf-random	0.143 (0.007)	0.840 (0.007)	17.955	3.15	21.539	1.58
xgboost-cox	0.020 (0.014)	0.877 (0.005)	9.073	1.59	1.098	0.080
nn-cox	-0.002 (0.012)	0.570 (0.109)	59.880	10.5	334.754	24.5
xgboost-aft	-7.40 (0.776)	0.875 (0.006)	28.666	5.03	0.807	0.059
Primary biliary cholangitis; death, n = 276, p = 19						
aorsf-fast	0.423 (0.031)	0.902 (0.022)	0.080	1.00	0.020	1.00
aorsf-cph	0.411 (0.032)	0.901 (0.022)	0.161	2.01	0.020	1.00
aorsf-net	0.405 (0.033)	0.900 (0.022)	16.130	201.4	0.020	1.01
cif-rotate	0.395 (0.042)	0.893 (0.023)	10.099	126.1	2.363	118.0
rsf-standard	0.383 (0.033)	0.888 (0.024)	0.111	1.38	0.040	2.01
obliqueRSF-net	0.360 (0.032)	0.900 (0.023)	122.137	1,525.3	2.067	103.3
aorsf-random	0.349 (0.026)	0.889 (0.021)	0.373	4.65	0.020	1.00
cif-standard	0.338 (0.033)	0.895 (0.026)	0.260	3.25	1.471	73.5
cif-extension	0.336 (0.031)	0.893 (0.024)	11.191	139.8	4.839	241.7
glmnet-cox	0.336 (0.050)	0.882 (0.029)	0.121	1.51	0.002	0.100
ranger-extratrees	0.264 (0.026)	0.886 (0.029)	0.030	0.377	0.041	2.05
xgboost-cox	0.242 (0.110)	0.875 (0.024)	4.640	58.0	0.002	0.100
nn-cox	-0.024 (0.019)	0.613 (0.174)	11.186	139.7	0.252	12.6
xgboost-aft	-0.969 (0.333)	0.877 (0.022)	9.772	122.0	0.006	0.300
Rotterdam tumor bank; death, n = 2982, p = 11						
aorsf-net	0.164 (0.012)	0.760 (0.009)	154.345	134.0	0.397	0.395

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
obliqueRSF-net	0.162 (0.010)	0.759 (0.009)	554.274	481.3	124.158	123.4
aorsf-cph	0.160 (0.012)	0.757 (0.010)	2.673	2.32	0.909	0.904
aorsf-fast	0.158 (0.013)	0.755 (0.010)	1.152	1.00	1.006	1.00
cif-standard	0.158 (0.010)	0.757 (0.009)	8.251	7.16	47.391	47.1
rsf-standard	0.156 (0.014)	0.754 (0.009)	3.058	2.66	0.277	0.276
aorsf-random	0.151 (0.010)	0.750 (0.010)	5.985	5.20	0.414	0.411
cif-rotate	0.150 (0.012)	0.752 (0.012)	34.744	30.2	29.541	29.4
ranger-extratrees	0.139 (0.005)	0.747 (0.009)	3.357	2.91	2.866	2.85
xgboost-cox	0.131 (0.014)	0.753 (0.009)	5.214	4.53	0.019	0.019
cif-extension	0.131 (0.005)	0.750 (0.009)	26.506	23.0	30.945	30.7
glmnet-cox	0.118 (0.009)	0.731 (0.010)	0.770	0.668	0.018	0.018
nn-cox	-0.003 (0.009)	0.521 (0.036)	17.492	15.2	8.753	8.70
xgboost-aft	-1.33 (0.121)	0.760 (0.007)	14.435	12.5	0.010	0.010
Rotterdam tumor bank; recurrence, n = 2982, p = 11						
obliqueRSF-net	0.147 (0.013)	0.736 (0.011)	547.423	368.6	134.826	288.4
aorsf-net	0.146 (0.014)	0.735 (0.011)	170.103	114.5	0.431	0.923
cif-standard	0.144 (0.013)	0.734 (0.011)	5.107	3.44	32.549	69.6
aorsf-cph	0.143 (0.014)	0.734 (0.011)	3.336	2.25	0.462	0.988
aorsf-fast	0.142 (0.014)	0.732 (0.011)	1.485	1.00	0.467	1.00
aorsf-random	0.139 (0.013)	0.730 (0.011)	4.762	3.21	0.428	0.916
rsf-standard	0.138 (0.014)	0.731 (0.011)	3.256	2.19	0.285	0.609
ranger-extratrees	0.135 (0.009)	0.734 (0.011)	4.162	2.80	3.054	6.53
cif-rotate	0.130 (0.012)	0.727 (0.011)	37.933	25.5	38.363	82.1
cif-extension	0.119 (0.007)	0.731 (0.011)	23.917	16.1	28.877	61.8
glmnet-cox	0.117 (0.009)	0.727 (0.010)	0.788	0.531	0.027	0.058
xgboost-cox	0.112 (0.008)	0.730 (0.011)	3.856	2.60	0.021	0.045
nn-cox	-0.002 (0.002)	0.536 (0.072)	23.903	16.1	11.126	23.8
xgboost-aft	-1.01 (0.126)	0.734 (0.011)	17.639	11.9	0.010	0.022
Serum free light chain; death, n = 7874, p = 10						
aorsf-fast	0.253 (0.017)	0.825 (0.009)	2.773	1.00	3.620	1.00
aorsf-cph	0.253 (0.016)	0.825 (0.010)	7.965	2.87	5.799	1.60
aorsf-net	0.252 (0.014)	0.823 (0.009)	341.019	123.0	5.805	1.60
glmnet-cox	0.250 (0.014)	0.820 (0.008)	1.330	0.480	0.093	0.026
obliqueRSF-net	0.249 (0.013)	0.821 (0.009)	1185.401	427.5	803.301	221.9
ranger-extratrees	0.246 (0.011)	0.821 (0.008)	17.067	6.15	13.889	3.84
rsf-standard	0.245 (0.015)	0.816 (0.009)	4.618	1.67	0.575	0.159
cif-standard	0.245 (0.013)	0.818 (0.009)	20.846	7.52	162.079	44.8

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-random	0.235 (0.013)	0.818 (0.010)	9.661	3.48	5.046	1.39
cif-rotate	0.228 (0.009)	0.819 (0.008)	71.056	25.6	137.166	37.9
cif-extension	0.203 (0.005)	0.821 (0.008)	46.895	16.9	184.798	51.0
xgboost-cox	0.095 (0.042)	0.824 (0.009)	6.667	2.40	0.098	0.027
nn-cox	0.004 (0.007)	0.664 (0.116)	30.033	10.8	32.325	8.93
xgboost-aft	-2.73 (0.324)	0.823 (0.009)	23.886	8.61	0.035	0.010
sim						
aorsf-net	0.044 (0.015)	0.649 (0.027)	227.140	172.6	89.309	1.82
aorsf-cph	0.043 (0.015)	0.653 (0.025)	3.021	2.30	51.086	1.04
aorsf-fast	0.039 (0.016)	0.654 (0.025)	1.316	1.00	48.973	1.00
aorsf-random	0.034 (0.011)	0.631 (0.027)	7.939	6.03	87.358	1.78
obliqueRSF-net	0.034 (0.012)	0.632 (0.030)	930.202	707.0	388.323	7.93
cif-standard	0.029 (0.011)	0.622 (0.029)	7.953	6.04	282.681	5.77
cif-rotate	0.029 (0.016)	0.614 (0.038)	342.777	260.5	714.891	14.6
rsf-standard	0.024 (0.010)	0.623 (0.021)	5.085	3.86	2.070	0.042
ranger-extratrees	0.021 (0.006)	0.637 (0.025)	4.566	3.47	6.406	0.131
cif-extension	0.018 (0.006)	0.617 (0.027)	107.534	81.7	1067.369	21.8
glmnet-cox	-0.003 (0.038)	0.637 (0.027)	0.552	0.420	1.597	0.033
xgboost-cox	-0.005 (0.036)	0.633 (0.029)	16.874	12.8	1.507	0.031
nn-cox	-0.032 (0.051)	0.639 (0.024)	37.356	28.4	20.600	0.421
xgboost-aft	-1.65 (0.119)	0.642 (0.025)	50.341	38.3	1.301	0.027
SPRINT; CVD death, $n = 9361$, $p = 174$						
aorsf-net	0.070 (0.007)	0.794 (0.012)	340.154	104.7	0.934	0.970
aorsf-cph	0.070 (0.006)	0.796 (0.011)	10.101	3.11	0.971	1.01
glmnet-cox	0.069 (0.012)	0.793 (0.010)	14.356	4.42	0.035	0.036
aorsf-fast	0.069 (0.006)	0.795 (0.010)	3.248	1.00	0.963	1.00
obliqueRSF-net	0.068 (0.005)	0.795 (0.012)	1222.666	376.4	1319.126	1,369.4
rsf-standard	0.064 (0.007)	0.785 (0.015)	5.389	1.66	0.654	0.679
cif-standard	0.061 (0.004)	0.795 (0.011)	50.214	15.5	199.723	207.3
cif-rotate	0.060 (0.005)	0.787 (0.010)	1115.642	343.5	139.444	144.8
ranger-extratrees	0.054 (0.004)	0.790 (0.013)	7.376	2.27	9.679	10.0
nn-cox	0.043 (0.010)	0.765 (0.016)	24.813	7.64	35.150	36.5
cif-extension	0.034 (0.002)	0.786 (0.011)	125.227	38.6	53.842	55.9
aorsf-random	0.026 (0.003)	0.743 (0.018)	6.889	2.12	1.101	1.14
xgboost-cox	0.010 (0.016)	0.796 (0.010)	7.945	2.45	0.033	0.034
xgboost-aft	-10.7 (0.988)	0.792 (0.011)	28.849	8.88	0.017	0.018
SPRINT; death, $n = 9361$, $p = 174$						

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
glmnet-cox	0.125 (0.010)	0.771 (0.010)	4.785	0.846	0.079	0.013
aorsf-cph	0.119 (0.007)	0.770 (0.009)	14.349	2.54	3.891	0.624
aorsf-fast	0.119 (0.007)	0.771 (0.008)	5.654	1.00	6.238	1.00
aorsf-net	0.115 (0.007)	0.769 (0.009)	663.058	117.3	4.744	0.760
obliqueRSF-net	0.114 (0.006)	0.768 (0.008)	3192.241	564.6	1289.532	206.7
rsf-standard	0.112 (0.006)	0.763 (0.008)	6.376	1.13	0.728	0.117
cif-standard	0.108 (0.006)	0.765 (0.009)	46.063	8.15	211.693	33.9
nn-cox	0.103 (0.011)	0.758 (0.009)	95.278	16.9	85.933	13.8
ranger-extratrees	0.098 (0.004)	0.758 (0.009)	9.978	1.76	11.653	1.87
cif-rotate	0.093 (0.005)	0.746 (0.009)	1057.791	187.1	188.939	30.3
cif-extension	0.056 (0.002)	0.748 (0.009)	138.879	24.6	110.890	17.8
aorsf-random	0.053 (0.003)	0.720 (0.010)	14.509	2.57	5.249	0.841
xgboost-cox	0.033 (0.022)	0.772 (0.008)	11.262	1.99	0.090	0.014
xgboost-aft	-4.40 (0.306)	0.772 (0.008)	32.854	5.81	0.719	0.115
Systolic Heart Failure; death, n = 2231, p = 41						
glmnet-cox	0.113 (0.015)	0.745 (0.012)	0.833	0.568	0.019	0.080
obliqueRSF-net	0.113 (0.014)	0.746 (0.012)	419.889	286.1	60.875	254.5
cif-rotate	0.113 (0.016)	0.741 (0.011)	72.369	49.3	22.019	92.1
aorsf-net	0.111 (0.015)	0.743 (0.012)	123.021	83.8	0.242	1.01
cif-standard	0.109 (0.013)	0.743 (0.012)	5.397	3.68	23.166	96.9
aorsf-fast	0.108 (0.018)	0.743 (0.011)	1.468	1.00	0.239	1.00
aorsf-cph	0.107 (0.016)	0.742 (0.011)	3.011	2.05	0.239	1.00
rsf-standard	0.105 (0.013)	0.736 (0.010)	3.688	2.51	0.734	3.07
cif-extension	0.095 (0.006)	0.744 (0.012)	31.103	21.2	18.063	75.5
xgboost-cox	0.092 (0.009)	0.745 (0.010)	4.791	3.26	0.010	0.042
ranger-extratrees	0.090 (0.009)	0.735 (0.012)	4.377	2.98	1.483	6.20
aorsf-random	0.081 (0.005)	0.729 (0.010)	3.206	2.18	0.231	0.964
nn-cox	0.079 (0.026)	0.712 (0.021)	24.930	17.0	5.889	24.6
xgboost-aft	-2.03 (0.186)	0.741 (0.008)	14.681	10.0	0.500	2.09
VA lung cancer trial; death, n = 137, p = 8						
aorsf-fast	0.198 (0.045)	0.789 (0.036)	0.058	1.00	0.013	1.00
aorsf-cph	0.197 (0.049)	0.789 (0.039)	0.104	1.78	0.013	0.994
aorsf-net	0.197 (0.044)	0.789 (0.037)	10.595	181.7	0.013	0.994
cif-rotate	0.196 (0.061)	0.782 (0.039)	5.268	90.3	1.148	87.7
rsf-standard	0.174 (0.048)	0.780 (0.042)	0.086	1.47	0.032	2.41
cif-extension	0.171 (0.047)	0.788 (0.036)	5.560	95.3	1.611	123.1
glmnet-cox	0.155 (0.031)	0.781 (0.038)	0.093	1.59	0.002	0.153

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-random	0.154 (0.046)	0.773 (0.042)	0.225	3.86	0.012	0.918
cif-standard	0.128 (0.037)	0.764 (0.037)	0.097	1.67	0.122	9.33
obliqueRSF-net	0.125 (0.035)	0.791 (0.029)	66.665	1,143.0	0.709	54.2
ranger-extratrees	0.091 (0.037)	0.779 (0.041)	0.025	0.433	0.031	2.37
xgboost-cox	0.041 (0.070)	0.736 (0.053)	0.809	13.9	0.002	0.153
nn-cox	-0.040 (0.041)	0.481 (0.058)	11.874	203.6	0.148	11.3
xgboost-aft	-0.042 (0.142)	0.748 (0.049)	7.545	129.4	0.006	0.459

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